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OPTIMIZATION OF CUTTING FORCE AND TOOL TEMPERATURE USING ANN BASED MULTI OBJECTIVE GENETIC ALGORITHMS IN TURNING HEAT TREATED BERYLLIUM COPPER ALLOY

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ABSTRACT

Economics of machining are mostly influenced by the cutting conditions [14]. The present study investigates the effect of cutting parameters- cutting speed, feed rate, depth of cut, and heat treatment of work material (Be cu alloy) in turning process using uncoated CBN cutting tool. Four outputs of the machining, among which heat treatment is categoric, studied. The outputs are cutting force and cutting tool temperature. Neural Network based Genetic Algorithm approach is used to study the performance characteristics and to find out the optimal cutting parameters of the turning process for heat treated Be-cu alloy. Annealed and hardened Beryllium Copper alloy are used for experiments. Feed rate and cutting speed play the key role in the process since the change of these parameters impart huge impact on cutting tool temperature change. Experimental results prove the effectiveness of this approach. In this study, the main cutting parameters that affect the cutting performance in turning operations and the best combination are determined.

KEYWORDS: Multi-Objective Optimization, Neural Networks, Cutting Force, Cutting Tool Temperature, Genetic Algorithm.

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Original Article

INTRODUCTION

Machining has been a challenged by the new generation of materials which are often difficult to machine. Thorough understanding of cutting mechanics can help to develop new methods, tools and machining processes. Copper alloy with beryllium has wide range applications due to its versatile properties on par with steels, with the additional properties of non sparking conductivity, under electric and magnetic field influence and aesthetic look.

The proposed study aims at evaluating the best process environment which simultaneously gives multi objective optimization. Turning involves different process parameters among which the most influential on the performance of the process are cutting speed, feed, depth of cut and type of work material. The work piece material, in this work is subjected to annealing and hardening, and is treated as two forms of material. From the past studies, it is provided that Beryllium copper alloy can be effectively machined with CBN tools.

Finally the effect of four input variables- cutting speed, feed, depth of cut, and work material on the selected output parameters (cutting force and cutting tool temperature) is studied in the study.

Optimal machining parameter determination is important for ensuring the efficiency of a machining process. Multi-Objective Optimization algorithms allow for optimizations that take into account multiple

objectives simultaneously. Criteria of system's efficiency are decided by the objective function that is to be either minimised or maximised. The proposed experimental study is categorised under the MOO where, Genetic Algorithm has been applied to solve the problem.

Literature Review

Vijayakumar et al. [1] applied ant colony algorithm for multi-pass turning parameters optimization, determined by minimizing the unit production cost, subject to various practical constraints. This paper proved that the ACO can obtain a near optimal solution in an extremely wide solution range within a reasonable computation time.

Saravanan et al. [2] applied simulated annealing and genetic algorithm to obtain the optimal machining parameters for continuous profile machining with regard to the minimum production cost subject to a set of constraints, cutting force, power constraints and tool tip temperature. It has been shown that simulated annealing performed slightly better than GA.

Sardiñas et al. [3] proposed genetic algorithms based multi-objective optimization technique to optimize the cutting parameters in turning processes: cutting depth, feed and speed. The model applied micro-genetic algorithm technique to obtain the non-dominated points and build the Pareto front. Tool life and operation time, were simultaneously optimized in this work, with remarkable advantages of multi-objective optimization approach. Car et al. [7] implemented Genetic algorithm for optimization of cutting parameters in CNC turning to minimize machining time and production cost.

Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) were implemented by Ganesan et al.[8] to resolve optimal cutting factors with respect to the minimum production time for continuous profile machining. The results obtained from GA and PSO showed that PSO generates better results than GA. Using this technique machining time could be further reduced.

Sahoo [10] applied Response Surface Methodology (RSM) to develop a mathematical model for surface roughness in terms of turning parameters based on experimental results and the same was used in Genetic algorithm (GA) to optimize the machining parameter. Sharma and Subbaiah [11] used artificial neural network (ANN) for cutting parameters modeling to predict surface roughness in CNC turning. This research concluded that ANN is a reliable method which could be conveniently applied to other metal cutting processes. Savadamuthu et al. [13] proposed a fuzzy control method in conjunction with the Taguchi-genetic method in optimizing cutting parameters in turning. The orthogonal array, signal-to-noise ratio, and the analysis of variance were employed to study the performance characteristics in turning AISI 1030 steel bars with TiN coated tools.

Methodology

Design of experiments technique is a powerful tool to carry out the modeling and analysis of the process variables and the response variables. The response variable is a function of the process variables, called design factors. The following features are of great importance in DOE:

- Minimize total number of trials
- The use of a mathematical formulation of many actions of the experimenter.
- The selection of a clear-cut strategy permitting the experiments to make substantiated decisions after each series of trials or experiments.

Design of Present Study

The design matrix with ranges is utilized looking into practical considerations of the Turning operation as in the table 1 given below:

Table 1: Input Factors and Levels

Factor	Name	Units	Type	Minimum	Maximum	Coded Values	
A	S	Rpm	Numeric	550	1800	-1.000=550	1.000=1800
B	F	mm/min	Numeric	60	400	-1.000= 60	1.000=400
C	D	Mm	Numeric	0.2	0.5	-1.000= 0.2	1.000=0.5
D	Wm		categoric	-1	1	{-1}= -1	{1}=1

Table 2: Experimental Details with Output Factors

Run	s (rpm)	f (mm/min)	d (mm)	wm	T (^{0}C)	F_c (KN)
1	1175	230	0.35	H	34.8	419.6
2	1800	400	0.356	H	40.4	915.7
3	1800	253.8	0.2	H	35.51	749
4	1175	230	0.35	H	34.8	419.6
5	1194.7	400	0.5	A	89.18	724.8
6	550	400	0.5	H	35.46	550.4
7	1175	230	0.35	A	52.57	187.8
8	550	400	0.5	H	35.46	550.4
9	1800	400	0.5	H	36.18	643
10	1175	145	0.5	A	48.68	65.11
11	550	400	0.2	H	20.05	556
12	1175	230	0.35	A	52.57	187.8
13	1800	400	0.5	A	104.3	1127
14	1300	400	0.2	H	38.47	1052
15	550	400	0.2	H	20.05	556
16	1175	230	0.35	A	52.57	187.8
17	1175	230	0.35	A	54	200
18	1175	230	0.35	H	34.8	419.6
19	1800	400	0.5	A	104.3	1127
20	550	60	0.2	H	32.91	161.5
21	1175	315	0.2	A	51.17	358
22	1800	400	0.2	A	88.05	1305
23	1175	230	0.35	H	34.8	419.6
24	1800	238.5	0.5	A	72	540.7
25	1487.5	230	0.5	H	27.83	200
26	1800	400	0.5	H	36.18	643
27	1800	400	0.2	A	88.05	1305
28	1300	400	0.2	H	38.47	1052
29	1175	230	0.35	H	34.8	419.6
30	550	60	0.2	H	32.91	161.5
31	1175	230	0.35	A	50	180
32	550	60	0.353	H	34.62	143.1
33	1175	230	0.35	A	52.57	187.8
34	1175	230	0.35	A	48	177
35	550	204.5	0.5	H	34.11	291.3
36	1800	400	0.2	A	88.05	1305
37	1175	230	0.35	H	34.8	419.6
38	1175	230	0.35	H	34.8	419.6
39	1175	230	0.35	A	56.4	190.78
40	1175	230	0.35	A	52	187.8
41	1175	230	0.35	H	34.8	419.6

Table 2: Contd.,

42	1175	230	0.35	A	52.57	187
43	1175	230	0.35	H	34.8	419.6
44	550	204.5	0.5	H	34.11	291.3
45	1800	253.8	0.2	H	35.51	749
46	1175	230	0.35	H	34.8	419.6

Neural Network Modelling and Validation

The concept of ANN is taken from analogy of biological neural networks. Many day to day problems that involve intelligence or pattern recognition are extremely complicated to automate. The neural network of an animal is a part of its nervous system, working with a network of specialized cells called neurons (nerve cells).

Neurons are extremely interconnected between the axon of one neuron and dendrite of another neuron. This connection is called synapse. Signals are propagated from the dendrites, through the cell body to the axon; from where the signals are propagate to all connected dendrites. A neuron can either slow down or stimulate a signal as per the requirement. Each artificial neuron receives signals from the environment, or other artificial neurons, gather these signals, and when fired transmits a signal to all connected artificial neurons.

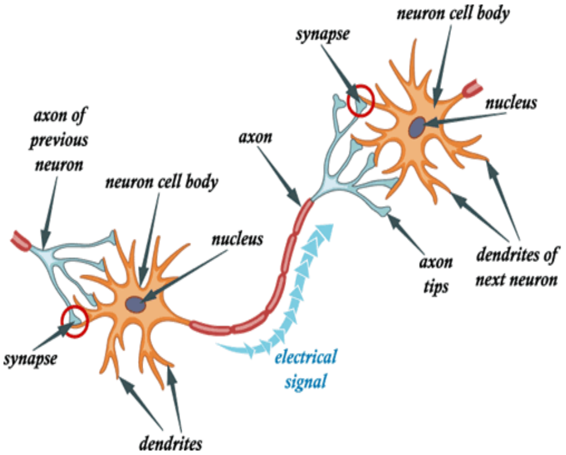

Figure 1: Data Transfer among Natural Neurons

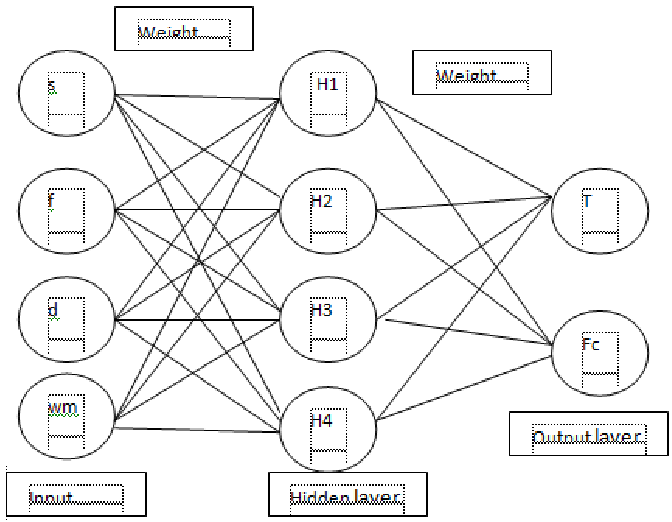

Figure 2: Artificial Neural Network Model for the Considered Factors

Important Specifications Used for Ann Modelling

Some of the important specifications of parameters that are frequently required throughout the modeling process have been shown in Table 3. (Data/ Data range indicate the values taken in the present problem.)

Table 3: Important Specification of Parameters used in ANN Modelling

S. No.	Parameter	Data/Data Range	Technique/Type of Parameter Used
1	Nos. of input neuron	4	
2	Nos. of output neuron	2	
3	Total nos. of exemplar	46	
4	Proportion of training, validation & testing data (%)	70:15:15	
5	Data normalization	0.05 - 0.95	Min-max data normalization technique
6	Weight initialization	-0.5 - 0.5	Random weight initialization technique
7	Transfer function	0 &1	Log-sigmoid function (for both hidden & output layer)
8	Error function		Mean squared error function
9	Mode of training		Batch mode
10	Type of Learning rule		Supervised learning rule
11	Stopping criteria		Early stopping

Experimental results were used to develop an ANN model for predicting MRR and surface roughness. In this work, four inputs and four outputs are considered as the data of ANN model with three numeric input variables speed, feed rate and depth of cut, one categoric input variable work material and the output variables T and F_c. A total of 46 experimental data is taken for neural network modeling, out of which 15% has been tested, 15% has been validated and remaining 70% is trained for the network. The summary of the network table (3).

Analysis of Performance Measures

Table 4: Training and Testing Information for Network

Net Information		
Name	Net Trained on T	Net Trained on Fc
Configuration	GRNN Numeric Predictor	GRNN Numeric Predictor
Independent Category Variables	1 (wm)	1 (wm)
Independent Numeric Variables	3 (s, f, d)	3 (s, f, d)
Dependent Variable	Numeric Var. (T)	Numeric Var. (Fc)
Training		
Number of Cases	39	39
Training Time	0.00.00	0.00.00
Number of Trials	95	69
Reason Stopped	Auto-Stopped	Auto-Stopped
% Bad Predictions (30% Tolerance)	0.0000%	0.0000%
Root Mean Square Error	0.6624	14.35
Mean Absolute Error	0.3233	10.05
Std. Deviation of Abs. Error	0.5782	10.24
Testing		
Number of Cases	7	7
% Bad Predictions (30% Tolerance)	0.0000%	0.0000%
Root Mean Square Error	3.844	116.23
Mean Absolute Error	2.847	49.39
Std. Deviation of Abs. Error	2.583	105.22
Data Set		
Name	T	Fc
Number of Rows	46	46

Table 4: Contd.,		
Manual Case Tags	NO	NO
R-Square (Training)	0.9942	0.9941
Root Mean Sq. Error (Training)	10.67	169.56
Root Mean Sq. Error (Testing)	10.57	162.50

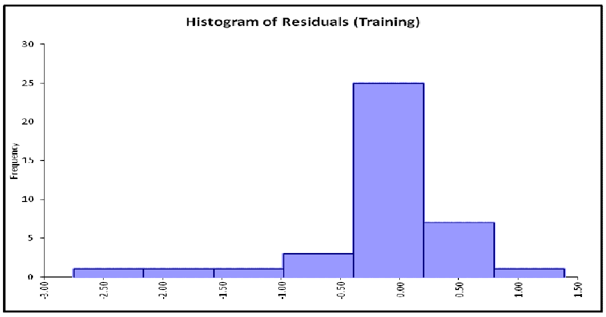

Figure 3: A. Error Histogram PLOT for Trained Data of T

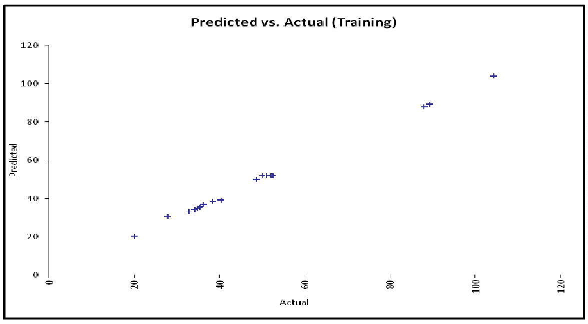

Figure 4: Predicted Versus Actual Plot for Trained Data of T

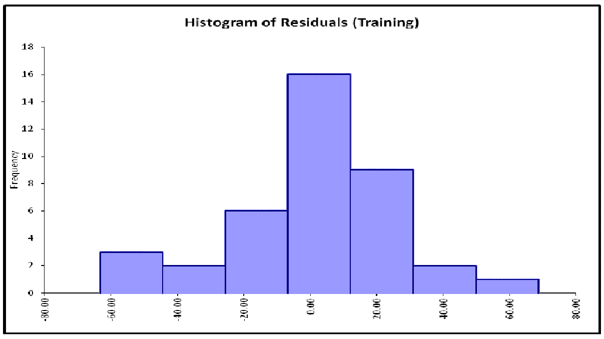

Figure 5: A. Error Histogram Plot for Trained Data of F_c

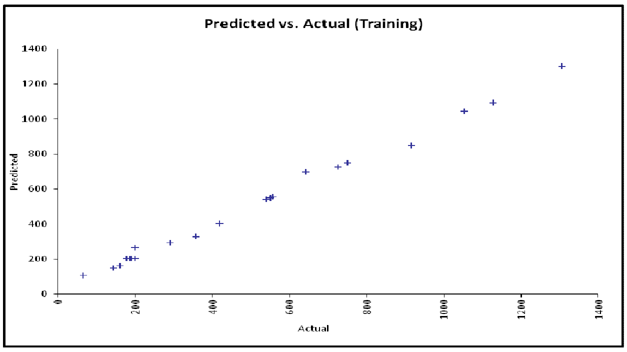

Figure 6: A. Error Histogram Plot for Trained Data of F_c

Table 5: Test Train Report for T and F_c

A:s	B:f	C:d	D:wm	Fc	Tag	Prediction	Good/ Bad	Residual	T	Tag	Prediction	Good/ Bad	Residual
1175	230	0.35	1	419.6	Train				34.8	train			
1800	400	0.356	1	915.7	Train				40.4	train			
1800	253.8	0.2	1	749	Train				35.51	train			
1175	230	0.35	1	419.6	Train				34.8	train			
1194.698	400	0.5	-1	724.8	Train				89.18	train			
550	400	0.5	1	550.4	Train				35.46	train			
1175	230	0.35	-1	187.8	Train				52.57	train			
550	400	0.5	1	550.4	Train				35.46	train			
1800	400	0.5	1	643	Train				36.18	train			
1175	145	0.5	-1	65.11	Train				48.68	train			
550	400	0.2	1	556	Train				20.05	train			
1175	230	0.35	-1	187.8	Train				52.57	train			
1800	400	0.5	-1	1127	Train				104.3	train			
1300	400	0.2	1	1052	Train				38.47	train			
550	400	0.2	1	556	Train				20.05	train			
1175	230	0.35	-1	187.8	Train				52.57	train			
1175	230	0.35	-1	200	Train				54	test	52.06	Good	1.94
1175	230	0.35	1	419.6	Test	402.92	Good	16.68	34.8	train			
1800	400	0.5	-1	1127	Train				104.3	train			
550	60	0.2	1	161.5	Train				32.91	train			
1175	315	0.2	-1	358	Train				51.17	train			
1800	400	0.2	-1	1305	Train				88.05	test	88.02	Good	0.03
1175	230	0.35	1	419.6	Train				34.8	train			
1800	238.5	0.5	-1	540.7	Train				72	test	79.85	Good	-7.85
1487.5	230	0.5	1	200	Train				27.83	train			
1800	400	0.5	1	643	Train				36.18	train			
1800	400	0.2	-1	1305	Train				88.05	train			
1300	400	0.2	1	1052	Train				38.47	train			
1175	230	0.35	1	419.6	Train				34.8	test	34.77	Good	0.03
550	60	0.2	1	161.5	Train				32.91	train			
1175	230	0.35	-1	180	Test	203.94	Good	-23.94	50	train			
550	60	0.353	1	143.1	Train				34.62	test	32.95	Good	1.67
1175	230	0.35	-1	187.8	Train				52.57	train			
1175	230	0.35	-1	177	Train				48	test	52.06	Good	-4.06
550	204.5	0.5	1	291.3	Train				34.11	train			
1800	400	0.2	-1	1305	Test	1301.02	Good	3.98	88.05	train			
1175	230	0.35	1	419.6	Train				34.8	train			
1175	230	0.35	1	419.6	Train				34.8	train			
1175	230	0.35	-1	190.78	Train				56.4	test	52.06	Good	4.34
1175	230	0.35	-1	187.8	Test	203.94	Good	-16.14	52	train			
1175	230	0.35	1	419.6	Train				34.8	train			
1175	230	0.35	-1	187	Train				52.57	train			
1175	230	0.35	1	419.6	Test	402.92	Good	16.68	34.8	train			
550	204.5	0.5	1	291.3	Test	291.66	Good	-0.36	34.11	train			
1800	253.8	0.2	1	749	Test	749.03	Good	-0.03	35.51	train			
1175	230	0.35	1	419.6	Train				34.8	train			

Analysis of Neural Network Model

Seven experiments in the design matrix were first tested at random for prediction using the network model and confirmation tests were performed for testing the significance of the model. At epoch 14, the best validation performance of 181873.6808 is observed for 20 iterations. Regression plots for the mean square error for trained, validated, test values and overall regression plot is shown in the figure (7). The R^2 values of 0.99 for all trained, validated, test and overall experimental runs prove the model validity.

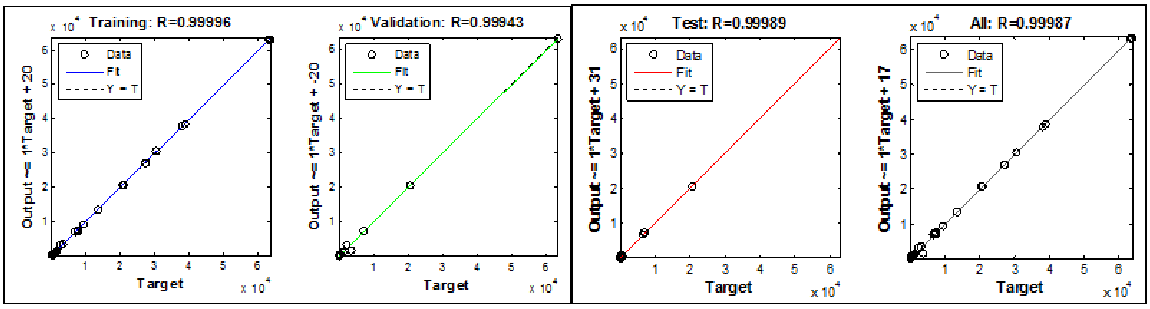

Figure 7: Correlation Coefficients for the Network

GA is a search technique for global optimization in a search space. As the name suggests it employs the concepts of natural selection and genetics using past information. It directs the search with expected improved performance and achieves fairly consistent and reliable results.

Simple GA Algorithm

- Provide an initial population of individuals.
- Calculate the fitness of all individuals.
- Repeat
    - Select fitter individuals for reproduction.
    - Recombine between individuals.
    - Mutate individuals.
    - Evaluate the fitness of the modified individuals.
    - Generate a new population
    - Until termination condition is satisfied (ex. 500 iterations).

Based on the above algorithm in this thesis NSGA II non-dominated sorting genetic algorithm is proposed. The presence of multiple objectives in a problem, in principle, gives rise to a set of optimal solutions largely known as Pareto-optimal solutions, instead of a single optimal solution. When such a method is to be used for finding multiple solutions, it has to be applied many times, hopefully finding a different solution at each simulation run.

Genetic Algorithm Based Multi Objective Optimization

Once the optimum solution is arrived, the algorithm terminates when one objective is taken. But there could be limited number of optimal solutions involve a multi objective problem. Goldberg proposed Multi objective optimization called Non-dominated Sorting Genetic Algorithm (NSGA-II), for obtaining non- dominated solutions. This algorithm contains several layers of classifications of the individuals and is applied to multi objective problems. The advantages of NSGA-II are;

- They are a population based search techniques, so global optimal solution is possible,
- They do not need any auxiliary information like gradients, derivatives, etc,

- They are easier to program and implement.

This algorithm uses the elite-conserving operator that favors the elites of a population by giving them a chance to directly move to the next generation. After the creation of two off springs using the crossover and mutation operators, they are compared with both of their parents to select the two best solutions among the four parent offspring solutions. In any multi objective optimization problem, there exist a number of solutions, which are of interest to designers and practitioners. Since no one solution is better than any other solution in the Pareto optimal set, it is also a goal in a multi objective optimization to find as many such Pareto optimal solutions as possible. Unlike most traditional search and optimization problems, GAs work with a population of solutions and thus are likely candidates for finding multiple Pareto optimal solutions simultaneously.

Genetic Algorithm Parameters

Sample size	=	18,	Crossover probability (Pc)	=	0.75,
Mutation probability (Pm)	=	0.01,	Number of generations	=	500.

The above parameters are fixed on the basis of literature review

Table 6

Population Type:	**Double Vector**	**Mutation Probability**	**0.1**
Population size :	60	**Fitness parameter :**	speed, feed, depth of cut, work piece material (coded to a numerical value: -1 for Annealed and 1 for hardened piece)
Length of Chromosome :	6	**Selection function:**	Tournament
Selection operator :	Rank order	**Mutation function :**	Adaptive feasible
Crossover operator :	Single point operator	**Crossover function:**	Heuristic
Crossover probability :	0.75	**Hybrid function:**	fgoalattain

Implementation of GA

Implementation plays a key role in the genetic algorithm. A problem can be solved once it is represented in the form of a solution string (chromosomes). The bits (genes) in the chromosome shall be binary, real integer numbers. In this paper, the cutting speed, feed rate, depth of cut and work material are considered to be the input parameters for the turning operation. Each of these primary variables is represented in a binary string format. The speed, feed rate, depth of cut and work material is represented as substrings in the chromosome. The total length of the string is 18 in which first 6 bits are used for each parameter. The strings (000000, 0000000, 000000, 000000) and (111111, 111111, 111111, 111111) represent the lower and upper limits of speed, feed, depth of cut and work material.

Initialization

A solution space of a “population size’ solution string is generated randomly between the limits of the speed, feed, depth of cut and work material. In this work the solution space size (population size) is considered as 60 as shown in Table **4.1**. Here the binary format population can be decoded by using the below formula is stated by Blickle (1995).

$$xi = xi(L) + \frac{xi(U)-xi(L)}{2n-1}$$ (Decoded decimal value)

where, x_i is the decoded speed or feed or depth of cut, xi(L) and xi(U) are the lower and upper limits of each of the input parameters respectively and n is the substring length (=6).

Evaluation

In GA, a fitness function value is computed for each string in the population and the objective is to find a string with the maximum fitness function value. It is often necessary to map the underlying natural objective function to a fitness function form through one or more mappings. GA always maximize the objective function (survival of fittest), Since we use a minimization objective function, the following transformation is used

$$f(x) = \frac{1}{1+g(x)}$$

Where, g(x) is the objective function (MRR/Ra/T/Fc) and f(x) is the fitness function. In the minimization problem the string which has the higher fitness value will be the best string. Fitness function for the present problem is written in M-file to call for in MOGA tool box in MATLAB. The fitness function is given as:

```
function y=finalopt(x)

{y(1)=63550-(13863.04+9016.27*x(1)+14104.40*x(2)+716.47*x(3)-6715.22*x(4)+10246.81*x(1)*x(2)+
1633.52*x(1)*x(3)-7480.92*x(1)*x(4)-2261.24*x(2)*x(3)-3932.25*x(2)*x(4)+104.52*x(3)*x(4)

-2099.33*(x(1))^2-100.22*(x(2))^2+190.80* (x(3))^2);

y(2)=+15.47+11.26*x(1)+12.69*x(2)-1.98*x(3)+6.36*x(4)+13.10*x(1)*x(2)+0.094*x(1)*x(3)+5.46*x(1)*x(4) -
3.70*x(2)*x(3)+5.73*x(2)*x(4)+1.53*x(3)*x(4)+4.42*(x(1))^2-0.022*(x(2))^2-0.23*(x(3))^2;

y(3)=+43.57+9.07*x(1)+13.42*x(2)+4.43*x(3)-8.78*x(4)+7.02*x(1)*x(2)-5.51*x(1)*x(3)-10.22*x(1)*x(4)
+3.48*x(2)*x(3)-9.34*x(2)*x(4)-5.721* x(3)*x(4)-5.01*(x(1))^2+0.75*(x(2))^2-0.97* (x(3))^2;

y(4)=303.49+254.8*x(1)+389.84*x(2)-45.75*x(3)+116.07*x(4)+169.79*x(1)*x(2)-148.7*x(1)*x(3)-229.61*
x(1)*x(4)-0.11*x(2)*x(4)-22.9*x(2)*x(4)-105.63*x(3)*x(4)-87.21*(x(1))^2 +33.28*(x(2))^2 +15.62*(x(3))^2; }
```

Selection and Reproduction

Reproduction selects good strings in a population and forms a mating pool. To get new roulette wheel selection chromosome this may be better than their parents. The reproduction operator is also called a selection operator.

Crossover

The strings to be crossed and the crossing points are selected randomly and crossover is done with a crossover probability. A single-point crossover is used in this work which is simple and easy to compute. The crossover probability (pc) is 0.75. The concept of crossover is explained below.

Before crossover [110010 – 00 | 0111 110100 – 01 | 0010]

After crossover: 1&2 means crossover takes place between 1st and 2nd string at (9 + 1)th cross site and after the (9 + 1)th bit all the information is exchanged between strings. The cross site number starts from zero. Hence cross site number

9 represents the 10th site. [110010 – 01 | 0111 110100 – 00 | 0010]

Mutation

Mutation is a random modification of a randomly selected string. Mutation is done with a mutation probability of 0.1. (pm=0.1)

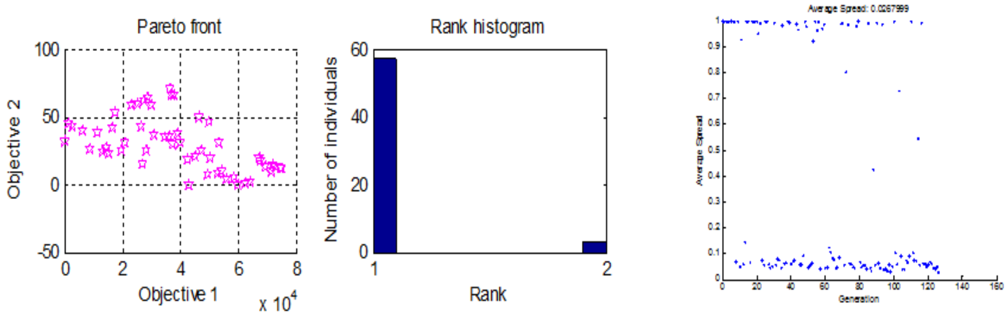

Figure 7: Average Spread Plot

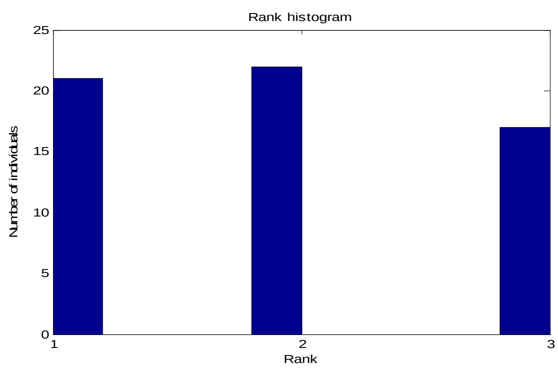

Figure 8: Rank Histogram Plot

Table 7: Optimal Set of Parameters (Coded) from MOGA

S (rpm)	F (mm/min)	D (mm)	wm	MRR (mm^3/min)	Ra (μ)	T (^{0}C)	Fc (KN)
1718.4	105.2	0.31	A	64171.84	2.18	32.3	10.31264
1716.7	106	0.29	A	62403.21	0.96	33.9	31.69292
1822.3	157.5	0.3	A	53065.38	8.05	42	198.5
1835.5	132.5	0.28	A	58384.14	5.2	37.8	140.8729
1772	134.3	0.28	A	56008.33	3.67	39.4	136.1479

RESULTS AND CONCLUSIONS

The proposed study developed the model for four different parameters namely speed,feed and depth of cut are as numeric factors and heat treatment (wm) as categoric factor for turning process on CNC LATHE on Beryllium Copper alloyin two forms (Annealed and Hardened) using Artificial Neural Network (ANN). The quadratic models have been validated with the regression and R-squared analysis (R^2 for the model =0.9987). It is found that the feed and depth of cut have less significant effect while speed and heat treatment have more significant effect on cutting temperature and cutting force. The percentage errors in all the responses after confirmatory tests were found to be desirable (<=7%). It can be concluded that models that are developed are much valid and can be used to predict the machining responses within the experimental region.

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